ELEN 199: Directed Research

Classification of Diseased Crop Images Using AlexNet

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I. Abstract

In vast fields filled with numerous crops, it is intensely laborious for farmers and workers to observe each crop and note both which ones are diseased, and are diseased in what way. It is also noteworthy that many farmers across the world have access to laptops that can perform artificial intelligence model training based on images that they can collect from their own farms, but that their computational capacities are limited due to financial restrictions. The focus of this project is to develop a trained AlexNet model that can accurately classify whether or not a crop is diseased and in what way, and do so under a low number of epochs and batches to simulate the computational restrictions of many international farmers. After modifying the number of epochs between 2 and 4, and the learning rates between 0.001, 0.0005, and 0.0001, our results showed that after running each trial variant three times, the model trained under 4 epochs with a learning rate of 0.001 was most accurate at 98.55%.

II. Motivation

It is important that our global food supply chain is constantly improved and optimized such that we can feed the most amount of people possible, and slowly take steps toward eliminating world hunger. Though many farmers in say India or Uganda are limited by their financial income, their overall income is increasing due to increased demands for global imports to say China or the United States. Some are able to buy webcams, 360-degree cameras, or even drones, and as such, them being able to use software that can improve the overall state of their farms through images is very powerful.

III. Dataset

For this project, we used a dataset containing over 87k images of both healthy and diseased crop leaves that were organized in 38 different classes, available on Kaggle. Scrolling through all of the images and their categories, I found that none were mislabeled. An initial issue was that the images were of size 235x235 where AlexNet expected sizes of 227x227. However, after importing the data into MATLAB, I created a transformation function that reduced all of the images to 227x227. For training and testing, the dataset was split between 80% train and 20% test.

Figure 1: Healthy apple and blueberry leaves example images

The 38 different classes included:

- Apple Scab
- Apple Black Rot
- Apple Cedar Rust
- Apple Healthy
- Blueberry Healthy
- Cherry Healthy
- Cherry Powdery Mildew
- Corn Gray Leaf Spot
- Corn Common Rust
- Corn Healthy
- Corn Northern Leaf Blight
- Grape Black Rot
- Grape Black Measles
- Grape Healthy
- Grape Leaf Blight
- Orange Haunglongbing
- Peach Bacterial Spot
- Peach Healthy
- Pepper (Bell) Bacterial Spot
- Pepper (Bell) Healthy
- Potato Early Blight
- Potato Healthy
- Potato Late Blight
- Raspberry Healthy
- Soybean Healthy
- Squash Powdery Mildew
- Strawberry Healthy
- Strawberry Leaf Scorch
- Tomato Bacterial Spot
- Tomato Early Blight
- Tomato Healthy
- Tomato Late Blight
- Tomato Leaf Mold
- Tomato Septoria Leaf Spot
- Tomato Spider Mites
- Tomato Target Spot
- Tomato Mosaic Virus
- Tomato Yellow Leaf Curl Virus

IV. Methodology

To simulate the computational restrictions of farmers, I limited the duration of AlexNet training. Using a constant batch-size of 200, I varied the number of epochs between 2 and 4, and the learning rates between 0.001, 0.0005, 0.0001. I averaged three tests of each variant, and the data to draw a conclusion. Below are examples from each test.

2 Epochs:

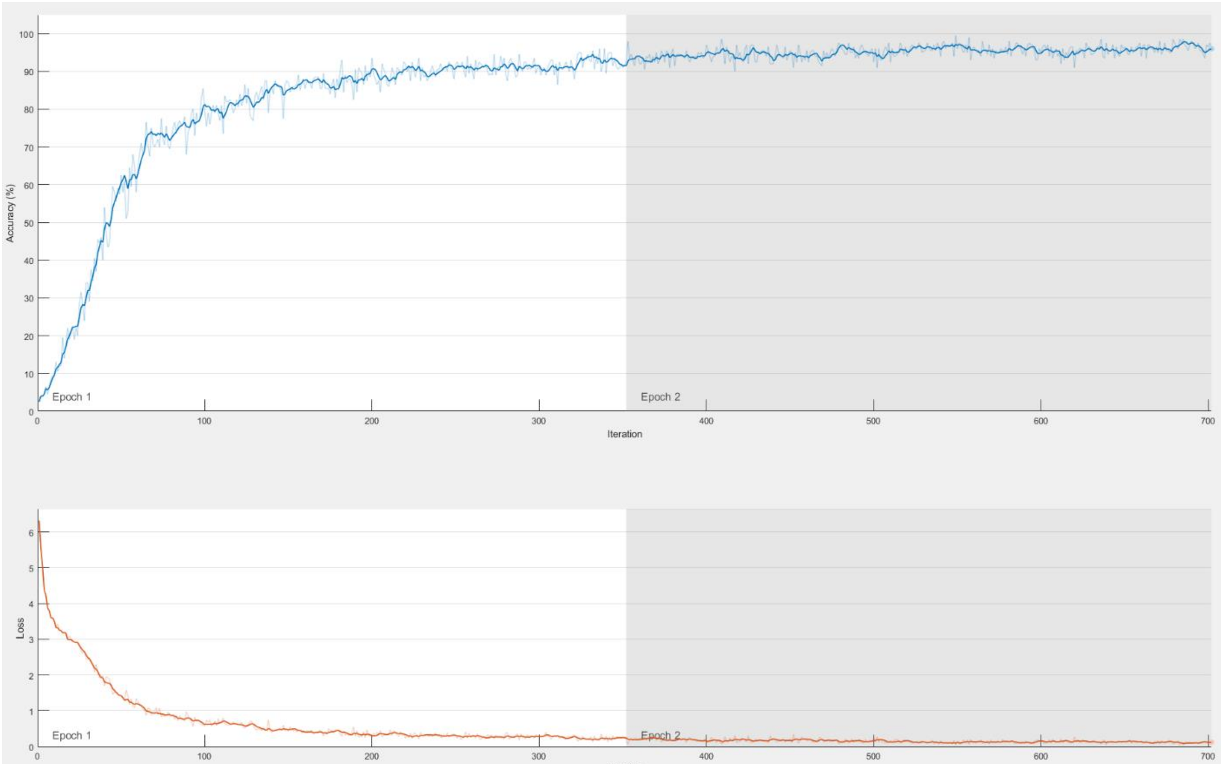

Figure 2: Graph of training accuracy, 2 epochs @ LR = 0.001

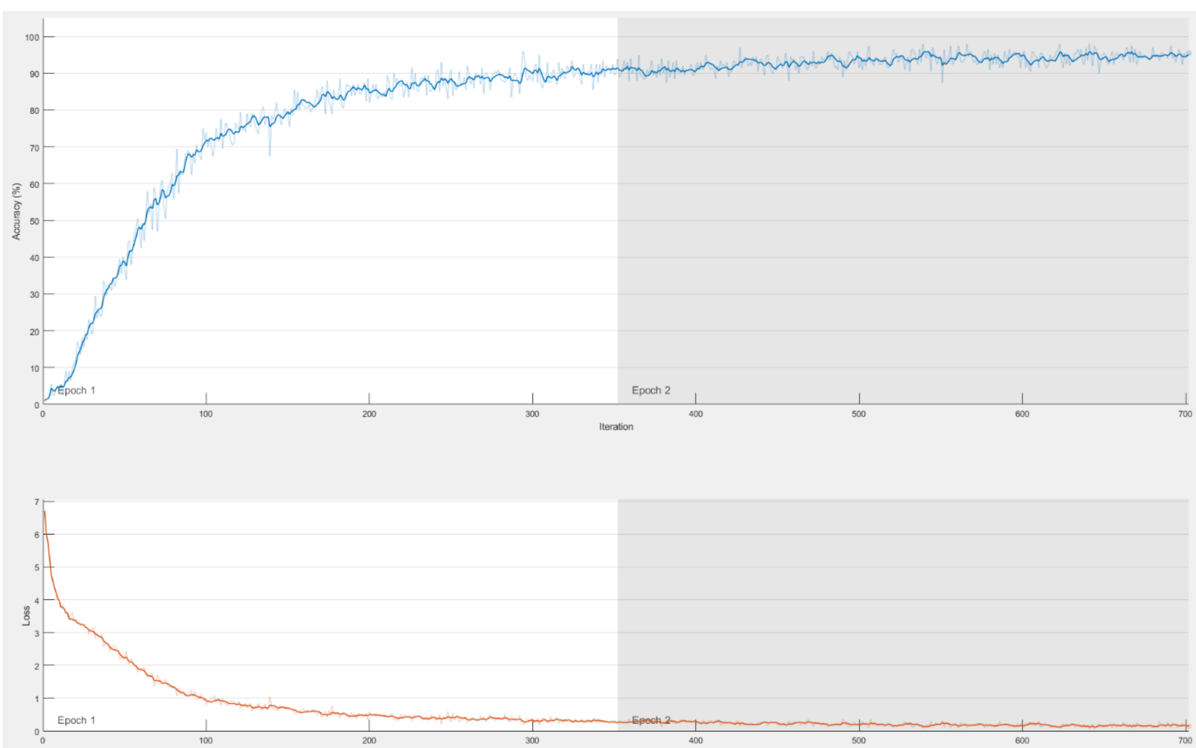

Figure 3: Graph of training accuracy, 2 epochs @ LR = 0.0005

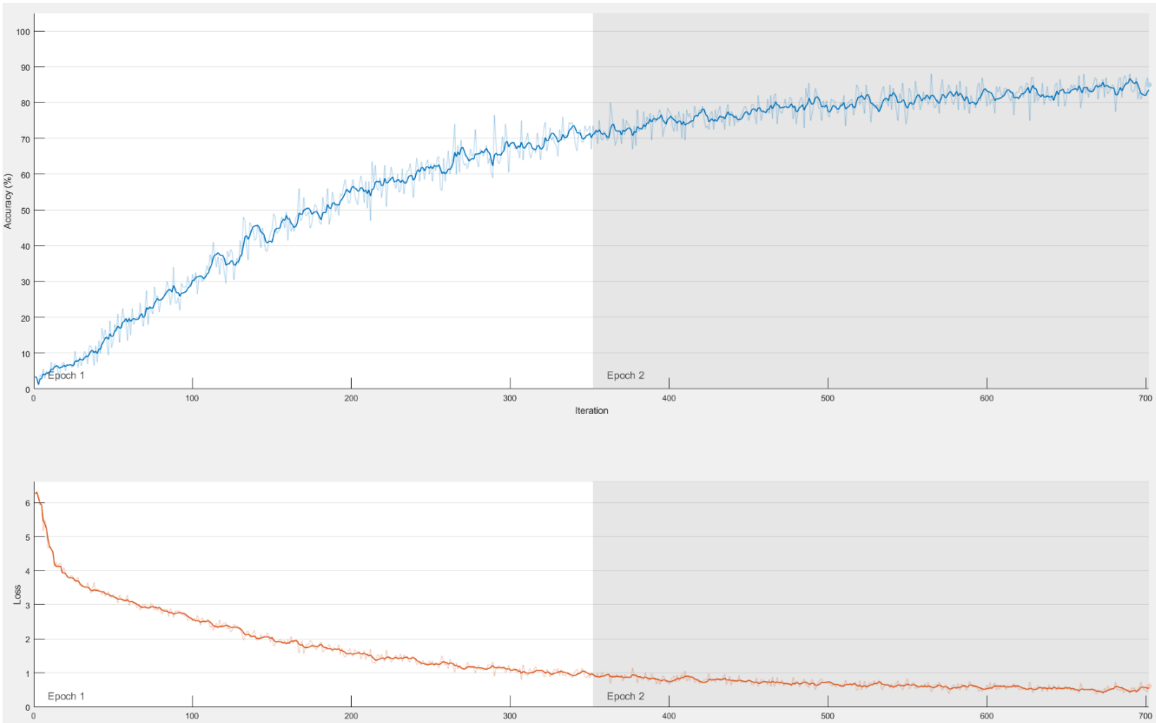

Figure 4: Graph of training accuracy, 2 epochs @ LR = 0.0001

As we can observe by the graphs, the model that initially learned the fastest was the one that used the learning rate of 0.001, and the one that learned the slowest had a learning rate of 0.0001. By general intuition, this makes sense. As smaller learning rates would make our model slower to converge to a higher accuracy over a lower number of epochs compared to models trained over a higher number of epochs, below is data that justifies this claim.

Epoch	Iteration	Accuracy 0.001	Accuracy 0.0005	Accuracy 0.0001
1	1	2.50%	1.00%	3.50%
1	50	62.50%	37.00%	13.50%
1	100	79.50%	74.00%	32.00%
1	150	87.00%	79.00%	44.50%
1	200	93.50%	82.00%	56.50%
1	250	92.00%	91.00%	63.00%
1	300	91.00%	88.00%	68.50%
1	350	91.00%	89.50%	73.50%
2	400	97.00%	92.00%	77.50%
2	450	95.50%	94.50%	75.00%
2	500	92.50%	91.50%	76.50%
2	550	96.00%	94.50%	76.00%
2	600	95.00%	95.00%	79.00%
2	650	96.60%	95.50%	81.00%

2	700	96.50%	94.50%	85.00%
2	702	95.00%	95.50%	85.00%

Figure 5: Table of accuracy scores compared against other learning rates over epochs

4 Epochs:

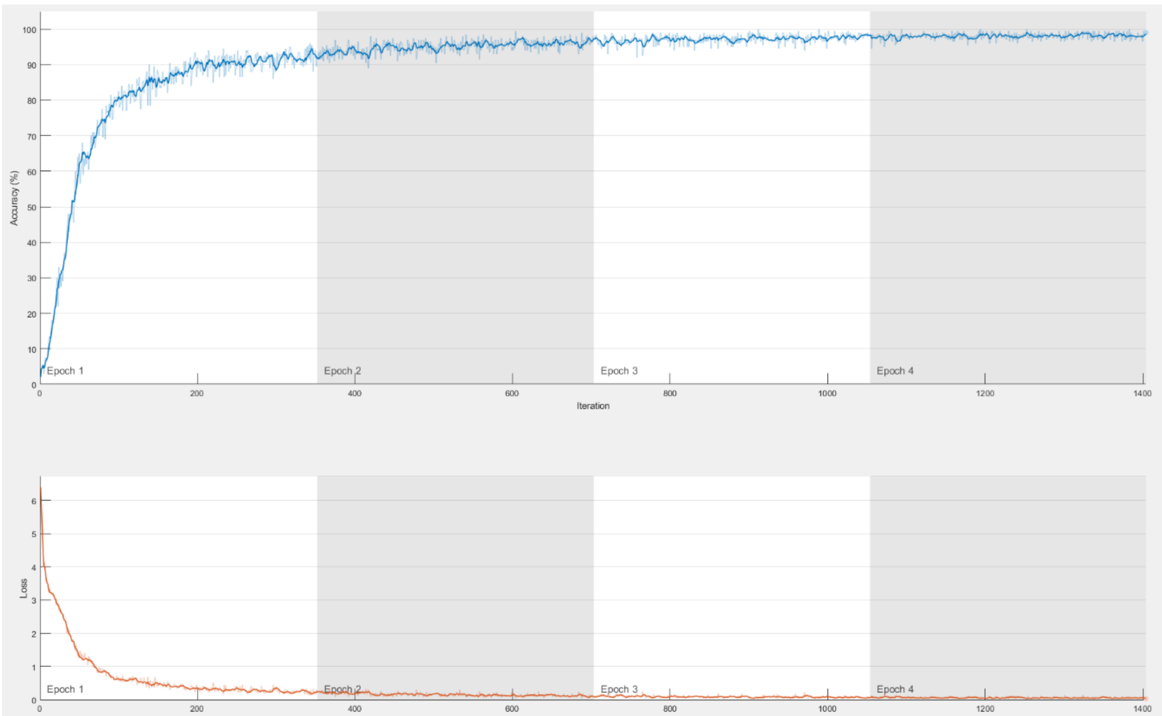

Figure 6: Graph of training accuracy, 4 epochs @ LR = 0.001

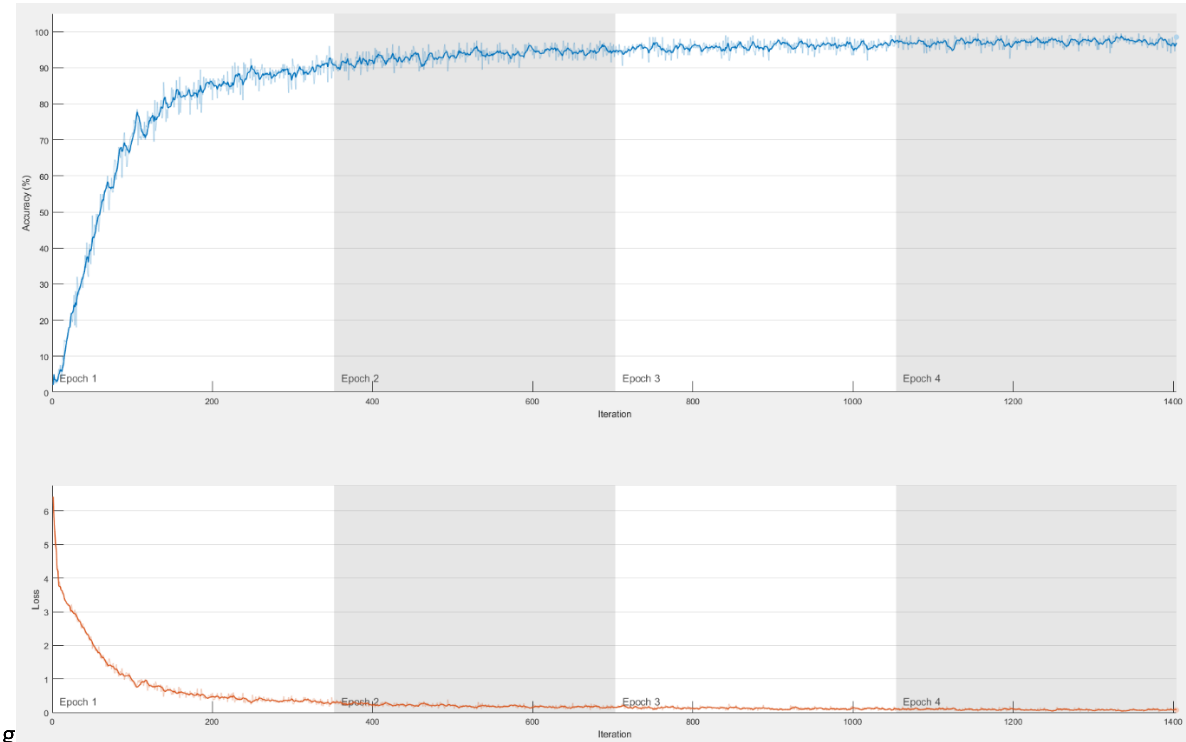

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Figure 7: Graph of training accuracy, 4 epochs @ LR = 0.0005

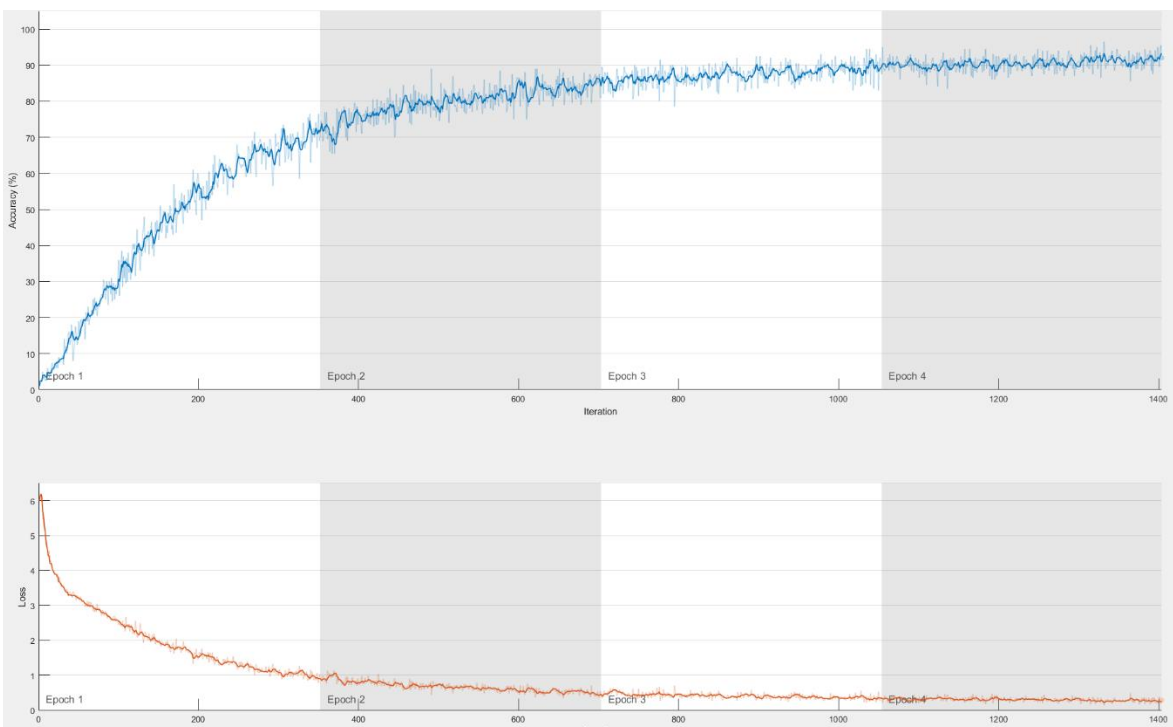

Figure 8: Graph of training accuracy, 4 epochs @ LR = 0.0001

Epoch	Iteration	Accuracy 0.001	Accuracy 0.0005	Accuracy 0.0001
1	1	2.00%	2.00%	1.00%
1	50	65.00%	49.00%	19.00%
1	100	82.50%	72.00%	36.00%
1	150	88.00%	80.50%	41.50%
1	200	92.00%	81.00%	58.50%
1	250	89.00%	86.50%	65.50%
1	300	88.00%	92.50%	68.50%
1	350	94.00%	92.50%	76.50%
2	400	91.50%	93.50%	75.00%
2	450	94.00%	92.00%	78.50%
2	500	94.00%	95.00%	80.50%
2	550	96.00%	92.00%	82.50%
2	600	95.00%	93.50%	85.50%
2	650	96.50%	92.00%	81.00%
2	700	96.00%	94.00%	85.50%
3	750	97.00%	98.50%	81.50%
3	800	95.00%	96.00%	85.50%
3	850	98.00%	96.00%	82.00%
3	900	97.00%	97.00%	88.00%
3	950	97.00%	96.00%	90.50%
3	1000	98.00%	96.00%	89.50%
3	1050	98.00%	96.00%	83.00%
4	1100	98.50%	96.50%	91.50%
4	1150	97.50%	98.50%	91.00%
4	1200	98.00%	97.50%	92.50%
4	1250	98.50%	95.50%	89.00%
4	1300	98.00%	98.50%	91.00%
4	1350	97.00%	96.50%	92.50%
4	1400	96.50%	96.00%	92.50%
4	1404	99.00%	98.50%	92.00%

Figure 9: Table of accuracy scores compared against other learning rates over epochs

To measure the total accuracy of each model after they were fully trained, we tested them against all test images and found their accuracies:

	2 Epochs	4 Epochs
LR = 0.001	97.88%	98.55%
LR = 0.0005	97.55%	98.42%
LR = 0.0001	92.80%	96.07%

Figure 10: Average accuracies of all variants of model trained

V. Conclusion

Given the accuracy of each of the models, it is clear that the most accurate model trained used a learning rate of 0.001 over 4 epochs. What we can observe is that the models that were trained with a learning rate of 0.0001 were the least accurate due to not being allowed more time to be trained with their smaller steps. However, we must notice that over such little epochs that we achieve over 90% accuracy. With that said, it is clear that if farmers were to train images they collected of their crops to classify diseases or crop variants, AlexNet would be a very efficient model for them to use.

Using these models generated, farmers could load them onto phones, drones, or laptops, and scan their fields to have a greater insight into the state of their farm.

VI. Future Work

Using my 2.6 GHz quad-core CPU instead of GPU to simulate resource constriction, a 2-epoch train on my laptop took a little over an hour, and a 4-epoch train took a little over two hours. As I did three variant 2-epoch trains three times, and three variant 4-epoch trains three times, total computation time took around 27 hours. In order to efficiently train more model variants at new learning rates and epoch numbers, I should transition my work to a more powerful desktop with a GPU that MATLAB could utilize. This would allow me to figure out that, given a large dataset of greater than 50k images, at what point should farmers limit the number of epochs that they use to train to prevent diminishing returns and wasted compute time.

Though AlexNet is obviously an efficient model, it would also be interesting testing it against other well-established models and comparing performance over the same learning rates and number of epochs.

VII. References

1. https://www.kaggle.com/vipoooool/new-plant-diseases-dataset
2. https://www.ifama.org/resources/Documents/v17i4/Lakner-Baker.pdf
3. https://www.mathworks.com/help/deeplearning/ref/alexnet.html